APPLICATION OF HEALTH EDUCATION PROGRAM BASED ON INTELLIGENT RECOMMENDATION ALGORITHM IN THE DEVELOPMENT OF SCHOOL-AGE CHILDEN'S HAND HYGIENE BEHAVIOR

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Abstract. The cultivation of hand hygiene behavior among school-age children is an important way to prevent the spread of diseases and ensure children's health. However, traditional health education methods lack personalized programs tailored to each child, which cannot effectively improve their hand hygiene awareness and behavior. In response to this issue, the study combines multi-objective particle swarm optimization algorithm to provide personalized hand hygiene behavior development recommendations for school-age children, improving their hand hygiene awareness and behavioral level. The study adopted multi-objective particle swarm optimization algorithm and convolutional neural network, combined with the personalized needs of school-age children and the goal of cultivating hand hygiene behavior, and proposed a health education plan based on intelligent recommendation algorithm. Through deep learning, match the hand hygiene needs of school-age children with corresponding health education plans to achieve personalized recommendations. The average accuracy of the health education recommendation plan for hand hygiene behavior cultivation of school-age children based on multi-objective particle swarm optimization algorithm reaches 99.07%. Meanwhile, after introducing convolutional neural networks, the feature matching error between the recommended scheme and school-age children ranges from 10-1 to 10-2. After testing, the designed algorithm performs more stably and has less fluctuations under different sparsity conditions. Health education solutions based on intelligent recommendation algorithms can provide personalized solutions for school-age children, effectively cultivate their hand hygiene behavior, and meet various health needs.

Key words: School age children; Hand hygiene behavior cultivation; Intelligent recommendation algorithm; multi-objective optimization; deep learning

1. Introduction. In today's digital age, with the continuous development of the Internet and big data technology, the application of intelligent recommendation algorithms in the field of health education is gradually receiving attention [1, 2]. Especially in the cultivation of hand hygiene behavior among school-age children, intelligent recommendation algorithms can provide personalized educational programs based on children's behavior and preferences, which helps to improve children's hand hygiene awareness and behavior development [3, 4]. Hand hygiene is one of the important ways to prevent the spread of diseases, especially among school-age children. Due to the complex environment and objects they come into contact with, the importance of hand hygiene is even more prominent. However, traditional health education methods often lack personalized programs tailored to each child, which cannot effectively improve their hand hygiene awareness and behavior [5]. Intelligent recommendation algorithms can provide customized hand hygiene education plans for each child by analyzing their behavior and preference data. Through deep learning and data mining techniques, we can understand children's acceptance of hand hygiene information, learning styles, and interests, thereby providing them with more appropriate educational content and methods. In view of this, the study comprehensively considers the personalized choices and reasonable healthy diet of school-age children, as well as the cultivation goals of hand hygiene behavior. The study uses multi-objective particle swarm optimization (PSO) algorithm to motivate the hand hygiene behavior of school-age children, improves the multi-objective PSO algorithm, and constructs a multi-objective optimization algorithm suitable for the hand hygiene behavior of school-age children. At the same time, it combines convolutional neural networks (CNN), A personalized intelligent rec-

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ommendation algorithm based on particle swarm optimization and deep learning for hand hygiene behavior cultivation of school-age children has been proposed to promote their hand hygiene behavior cultivation. The research structure is mainly divided into four parts. The first part is a summary of relevant research results; The second part is the design of a health education solution based on intelligent recommendation algorithms; The third part is to verify the effectiveness of the algorithm; The final part is the research summary.

2. Related work. With the improvement of people's living standards, people pay more and more attention to the quality of life. Various recommendation systems are widely used in humans. How to improve the accuracy of recommendation is a key issue. To improve the accuracy and user satisfaction of the recommendation system, Janakiraman et al. proposed technologies such as ant colony and particle swarm optimization to optimize the recommendation algorithm. The recommendation algorithm of PSO is superior to other traditional algorithms, with higher performance and Accuracy [6]. To prevent the sudden appeal of diabetes-related complications, Tabassum N et al. proposed an expert recommendation system using fuzzy logic to determine individual dietary needs at the micro and macro nutritional levels. The results showed that the system can recommend the best diet plan for diabetes control. Prevention of complications is very effective [7]. In order to choose an appropriate method to build an interactive news data heterogeneous graph with an appropriate learning mechanism, M Ma et al. raised a news personalized recommendation system on the ground of a graph-based action-aware network, and the results showed that the system can focus on different users. Different degrees of user recommendation news [8]. To shorten the search room of similar users or items in social networks, Berkani proposed a personalized item recommendation combining social filtering algorithm and traditional user-based collaborative filtering algorithm. This method can effectively cut down the search space [9]. Benkessirat et al. proposed a recommendation system that uses clustering to improve the collaborative filtering algorithm in order to help users find joy that better match their personal data. Compared with classical collaborative filtering and collaborative filtering based on k-means, the proposed method significantly enhances the recommendation efficiency [10]. To address the matter of low accuracy of traditional recommendation methods and the lack of consideration of information, Zhang et al. suggested a multi-dimensional comprehensive recommendation method. This could lift the recommendation accuracy [11]. Cao B and others artificially solved the problem of big data overload and designed a distributed parallel evolutionary algorithm based on non dominated sorting and crowding distance. It discovered network nodes with fewer visits in a personalized way, thereby alleviating the pressure of data overload. The results showed that this method has good performance and efficiency [12].

CNN, as a type of neural network that specializes in processing data with similar grid structure, is widely used because of its good accuracy and efficiency in processing large data sets. To enable users to effectively search for same, related and diverse Dunhuang mural images, Zeng et al. proposed a CNN model tuned in the data set of Dunhuang murals. The finely tuned ResNet152 is the best choice for searching for similar images at the visual feature level, while improving the diversity of search results [13]. Wang et al. studied the robustness of graph convolutional network (GCN), and proposed a new "false node attack" to attack GCN by adding malicious fake nodes. The results showed that non -target attacks reduced the GCN accuracy. Up to 0.03, targeted attacks achieve a 78% successful rate on a group of 100 nodes, and an average success rate of 90% when attacking a single targeted node [14]. W El-Shafai et al. raised a CNN-based SIGTra hybrid module to accurately display the main features of pneumonia and COVID-19 diagnostic medical images, and the results showed that the SIGTra is compatible with other related CNN models for COVID-19 detection. Compared with it, it shows better performance in terms of precision, sensitivity and accuracy [15]. For solving the problem of limited prediction-accuracy of traditional network security situational awareness, Chen constructed a RBF neural network prediction model based on SA-HHGA optimization. The results showed that the predicted situation value and the actual situation value of the optimized RBF in 15 samples. It is very close and has a good predictive effect [16]. For improving the data embedding ability of the modification-free steganography algorithm (MFS), JB Wu et al. designed a semi-structured MFS combined image classification and CNN. It has great anti-attack capacity and can improve Hidden ability [17]. Zhang Q et al. designed a robust deformable denoising cellular neural network to address the issue of convolutional operations potentially altering noise distribution in image denoising. The network extracts noise features through deformable blocks, promotes contextual interaction with enhanced blocks, and solves long-term dependency problems with residual blocks. The results show that the model performs well in both qualitative and quantitative analysis [18].
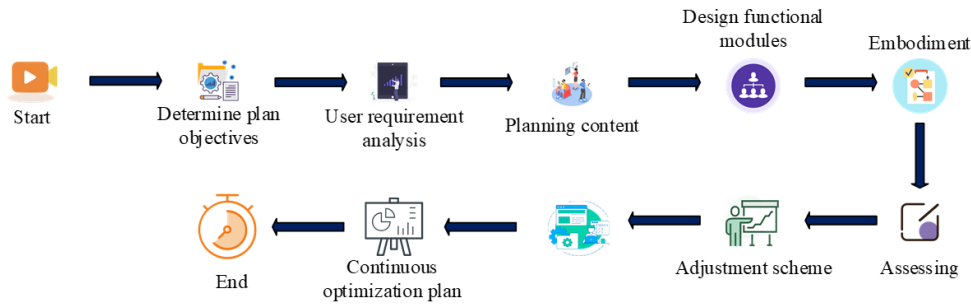
Fig. 3.1: Framework of Health Education Program for Hand Hygiene Training of School-age Children

To sum up, at this stage, abundant scholars have contributed to the application of various recommendation systems and CNN from various aspects. However, there are still relatively few personalized intelligent recommendation programs for cultivating children's hand hygiene behavior and health. Therefore, this study combines the feature extraction and representation methods of children's hand hygiene behavior data with multi-objective PSO algorithm, and proposes a recommendation algorithm for children's hand hygiene behavior development that combines deep learning and multi-objective optimization to provide personalized hand hygiene behavior development recommendations.

3. Methods. With the increasingly prominent issue of cultivating children's hand hygiene behavior, users and intelligent recommendation systems are facing increasing challenges in seeking effective solutions. In order to design a health education program suitable for cultivating children's hand hygiene behavior, a health education program based on intelligent recommendation algorithms was studied and constructed. CNN was introduced to establish a health education program for cultivating hand hygiene behavior among school-age children based on deep learning, in order to help them develop good hand hygiene habits.

3.1. Design of a health education program for cultivating hand hygiene behavior among school-age children. School-age children are in a critical period of growth and development, and their immune system is not yet fully mature, making them susceptible to infection. Developing hand hygiene behavior is one of the important ways to prevent the spread of diseases and is of great significance for protecting children's health. Therefore, it is necessary to design a health education program specifically aimed at cultivating hand hygiene behavior among school-age children. This program aims to help school-age children develop correct hand hygiene habits and improve their health level through education and training [19]. Based on the needs and goals of school-age children, a health education program for hand hygiene training of school-age children is designed. The framework is shown in Figure 3.1.

In Figure 3.1, the scheme first clarifies the objectives and specific real-time plan of the scheme. Conduct user needs analysis based on the goals to understand children's hand hygiene habits, cognitive abilities, and learning styles. And according to user needs, plan content such as hand hygiene knowledge, hand hygiene animations, hand hygiene games, and hand hygiene songs [20]. In this section, attention needs to be paid to the diversity, interest, education, and systematicity of the content to attract children's attention and enhance their learning interest. At the same time, design the functional modules of the system based on the content of the plan and the target user group, including learning mode, testing mode, and interactive mode. In functional design, attention should be paid to the practicality, ease of use, and scalability of functions to meet user needs while providing a good user experience. The program comprehensively considers the physical and mental characteristics, cognitive ability and behavior habits of school-age children to enhance their hand hygiene awareness and ability, and prevent and control the occurrence and spread of infectious diseases. Its goal is to cultivate good hand hygiene habits, and through systematic education and training, it helps school-age children establish good hand hygiene habits and enhance their awareness and ability of hand hygiene.
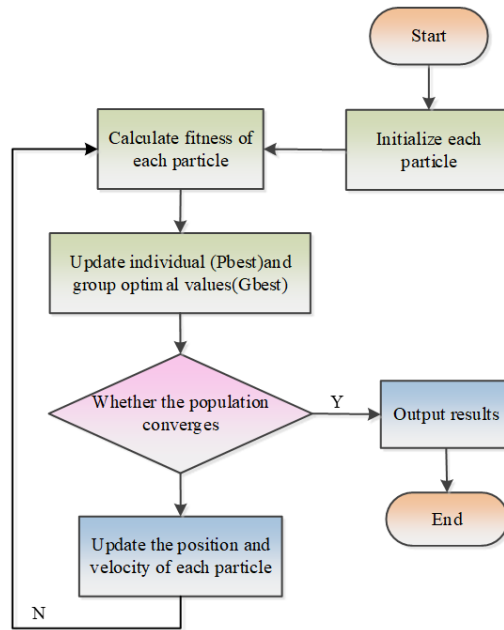
Fig. 3.2: PSO algorithm process

3.2. Design of multi-objective optimization algorithm for cultivating children's hand hygiene behavior based on particle swarm optimization. Although a health education program has been designed to cultivate hand hygiene behavior among school-age children, there are individual differences among school-age children, including age, gender, cognitive abilities, and learning styles. Therefore, it is necessary to provide more personalized and differentiated education tailored to the characteristics and needs of different children, and research the use of deep learning algorithms to optimize and improve the designed health education plans. In deep learning algorithms, the PSO is characterized by simplicity and fast convergence speed. The specific process is Figure 3.2 [21].

As shown in Figure 3.2, the Global-best solution (gBest) on single-objective optimization can be obtained through the PSO algorithm when the number of particle swarms is constant. However, when the optimization objectives become multiple, the PSO cannot complete the choice of the optimal position of the group among multiple individuals, because there are multiple optimal positions of the group in multi-objective optimization. To address this issue, the study put forward a multi-objective particle swarm optimization (MOPSO) built on the PSO to select a leader according to the degree of congestion in the optimal set [22]. The MOPSO includes five key elements, which are the initialization of the particle space, the topology of the particle neighborhood, the inertia weight, the maximum velocity of the particle, and the stopping criterion. The specific flow chart is Figure 3.3.

As shown in Figure 3.3, in the needs analysis of hand hygiene education programs for school-age children, multiple aspects of children are involved, including their hand hygiene habits, cognitive abilities, and learning styles. In order to balance multi-objective optimization and each nutrient, further research is needed on the definition rules of the five key elements of MOPSO. First of all, the research selects the particle space that includes aspects such as hand hygiene habits, cognitive abilities, and learning styles as the localization scope. The size of the particle swarm is N. Binary particles are used to initialize the initial velocity. The calculation method is shown in formula 3.1.

$$if(v_{id}^0 = max(v_{id}^0)), then \quad x_{id}^0 = 1, else \quad x_{id}^0 = 0 \tag{3.1}$$

In formula 3.1 v_{id}^0, is the initial velocity, x_{id}^0 and is the initial position. Then find the individual best

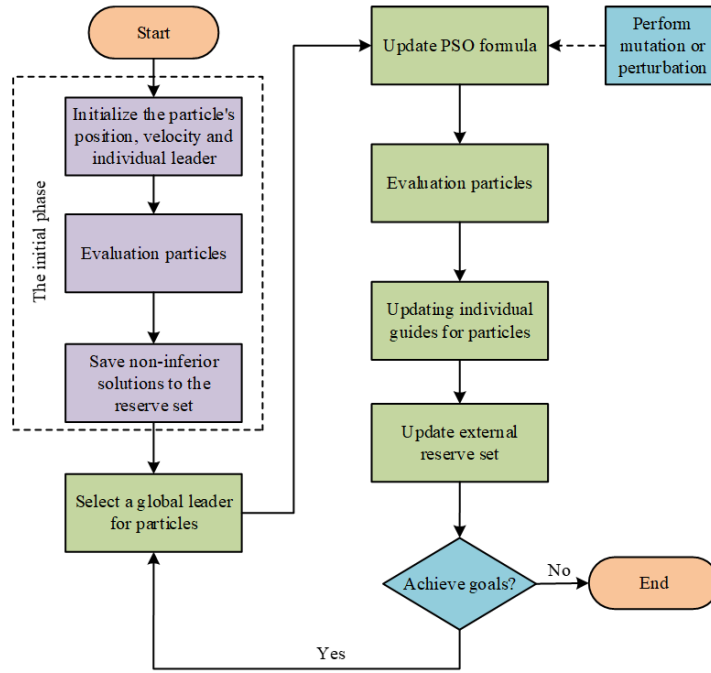Chong Li, Linghong Wang, Chao Dong, Zhaoxuan Meng

Fig. 3.3: MOPSO process

particle (pBest) value of each particle, and define an objective function suitable for hand hygiene behavior. This function can evaluate whether children's hand washing habits meet hygiene standards based on indicators such as hand washing time and frequency. The objective function should be consistent with the evaluation criteria for hand hygiene behavior in school-age children. By calculating the objective function value of each particle, the optimal particle, namely the optimal hand washing time and frequency, can be found. Comparing the optimal position value of the objective function of the historical best position adaptation value, and updat the one with the higher fitness value is updated as the historical best position, calculated as formula 3.2.

$$
\begin{cases}
pBest_i = (p_{i,1}, p_{i,2}, \ldots, p_{i,D},) \\
if \quad f(x_{id}) < p_{id}, then\, p_{id} = x_{id}, else\, p_{id} = p_{id} \\
if \quad f(x_i) < pBest_i, then \quad pBest_i = p_{id}, else \quad pBest_i = pBest_i
\end{cases}
\tag{3.2}
$$

Equation 3.2 $pBest_i$ is all the best positions that the particle-i has experienced in space, p_{id} represents the individual optimal position of particle i in d-dimensional space, x_{id} represents the current position of particle i in d-dimensional space, and $f(.)$ represents the evaluation function used to calculate the fitness of particle position. Find a global value from the calculated individual fitness value and compare it with the historical storage, update the global optimal solution to obtain the best balance of human nutritional needs, and the calculation is shown in formula 3.3.

$$
\begin{cases}
g_d = min(pBest_i) \\
gBest = (g_1, g_2, \ldots, g_D)
\end{cases}
\tag{3.3}
$$

$gBest$ in equation 3.3 is the best position that the population-d has experienced in the dimensional space component, which g_d is the that of the same in the space. Then, the contraction factor D is introduced to obtain a better solution to improve the shortcoming of the slow convergence speed of the PSO, and the calculation
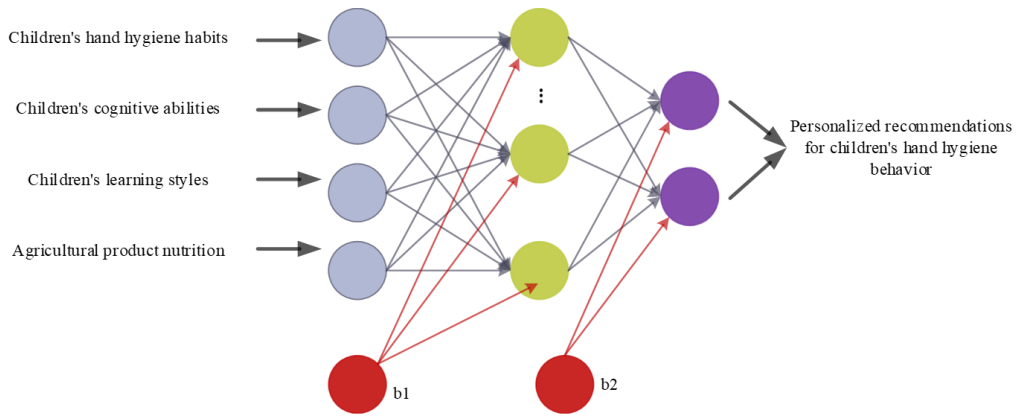
Fig. 3.4: CNN neural network structure diagram

formula of the update speed of the dimensional space component i of the particle is obtained d as formula 3.4.

$$\begin{cases} v_{id}^k = W[v_{id}^k + c_1 r_1 (pBest_{id} - x_{id}^k) + c_2 r_2 (g_d - x_{id}^k] \\ W = \frac{2}{|2-c-\sqrt{c^2-4c}|}, c = c_1 + c_2, c > 4 \end{cases} \tag{3.4}$$

In formula 3.4 c_1 , , c_2 is the learning factor, $c_1 = c_2$ and it is between 0 and 4; the contraction factor w is the c_1, c_2 restricted inertia weight. The velocity of the dimension changes during the update is in $d[-v_{min,d}, v_{max,d}]$ the range, when, $v_{id} > v_{max,d} v_{id} = v_{max,d}$. To further update the position of the dimensional space component i of the particle d, the calculation formula is shown in formula 3.5.

$$x_{id}^{k+1} = x_{id}^k + v_{id}^k \tag{3.5}$$

In formula 3.5, x_{id}^k and v_{id}^k are the d-th dimensional component of the vector position in the k-th iteration of particle i and flight velocity of particle i in the k-th iteration. During the update the position of the dimension changes in $d[x_{min,d}, x_{max,d}]$ the range, when, $x_{id}^k > pBest_{id} x_{id}^k = pBest_{id}$. At this point the value is updated k, set $k = k + 1$ until iterations equal max iterations to complete the algorithm steps.

3.3. Design of personalized recommendation algorithm for children's hand hygiene behavior development based on multi-objective optimization. Due to the different hand hygiene habits and cognitive abilities of each school-age child. Therefore, it is necessary to design personalized recommendations based on children's characteristics to meet children's needs. The research uses CNN to extract and intelligently recommend personalized health education plans [23]. CNN is divided into three parts: local receptive field, shared weight and pooling. It studies the problem of using CNN's forward and backward algorithms to adjust and update people's needs as time changes, and uses response error calculation to solve the output structure. The result deviates greatly from the user's own needs. First, personalized data on hand hygiene habits, cognitive abilities, and learning styles of school-age children are input into the input layer and standardized to unify units and formats [24, 25]. Then use the convolution layer to extract behavioral features, realize data processing and compression, and complete the preliminary screening process of AP. When the hand hygiene behavior data of school-age children is used as input, the personalized recommendation for cultivating children's hand hygiene habits are output, the hidden layer's node amounts are 4, 2, 3 hidden layers, and bias items, the specific CNN neural network structure is shown in Figure 3.4.

To provide users with a variety of choices, the research pushes different children's hand hygiene behavior development plans to users at the same time, and performs weighted summation of the non-dominated solutions
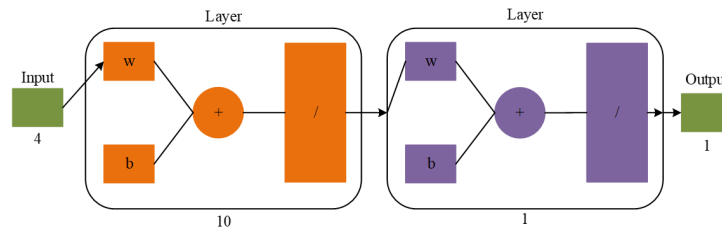
Fig. 3.5: CNN neural network specific structure diagram

that cannot be judged according to the weight. The calculation is formula 3.6.

$$F(x) = \sum_{i=1}^{n} \omega_i \times f_i(x) \tag{3.6}$$

In formula 3.6, $\omega_1, \omega_2, \ldots, \omega_n$ it is n the weight of the th behavior development plan, $f_i(x)$ which is n the fitness of the behavior development plan. In the calculation process, the research proposes a preference strategy to solve the situation that the user cannot provide weights. First, find all the solutions and perform a fast non-dominated sorting to divide the levels. For the non-dominated solutions of the same level, the user's input order of each behavior development plan is used as the preference tendency, and the order is reduced $\omega_1 > \omega_2 > \ldots > \omega_n$. The range U is determined according to the number n of agricultural product combinations, and the calculation is shown in formula 3.7.

$$U \in (0, U_{max} = \frac{2}{n(n-1)}, \quad n = 1, 2, ,\ldots \tag{3.7}$$

To sum up, the above-mentioned research input a large number of user orders and matched personalized solutions more suitable for learning hand hygiene habits and cognitive abilities through CNN self-learning, and realize the multi-objective personalized intelligent recommendation for hand behavior development in school-age children. The CNN input layer is set with 4 neurons, and the hidden layer is set with 3 neurons. The specific CNN structure is shown in Figure 3.5.

As shown in Figure 3.5, the application of CNN in the recommendation for children's hand behavior development. In summary, the personalized recommendation algorithm design for children's hand behavior development based on multi-objective optimization and deep learning has been completed.

4. Conclusion. The user's choice of an appropriate recommendation scheme is essentially a matching process between user needs and information on hand hygiene behavior cultivation for school-age children [26, 27, 28]. Users judge whether the recommended scheme meets their needs based on the intelligent recommendation algorithm, content, and the goal of cultivating hand hygiene behavior among school-age children, and ultimately choose a suitable health education plan. To verify the accuracy of the health education scheme based on intelligent recommendation algorithms in the cultivation of hand hygiene behavior among school-age children, this part focuses on the design of the convergence and distribution of non-inferior solutions of the algorithm on two-dimensional test functions, further testing the accuracy of the personalized intelligent recommendation scheme for hand hygiene behavior cultivation of school-age children based on CNN.

4.1. Performance analysis of hand hygiene behavior cultivation in MOPSO school-age children. For verifying the effect of intelligent recommendation algorithms for cultivating hand hygiene behavior among school-age children, user data was collected, such as age, gender, and hand hygiene behavior level of participating children, as well as relevant health education data, such as hand hygiene behavior goals, effectiveness evaluation, and learning feedback. From the experimental data studied, the determination of the maximum iteration value is carried out.
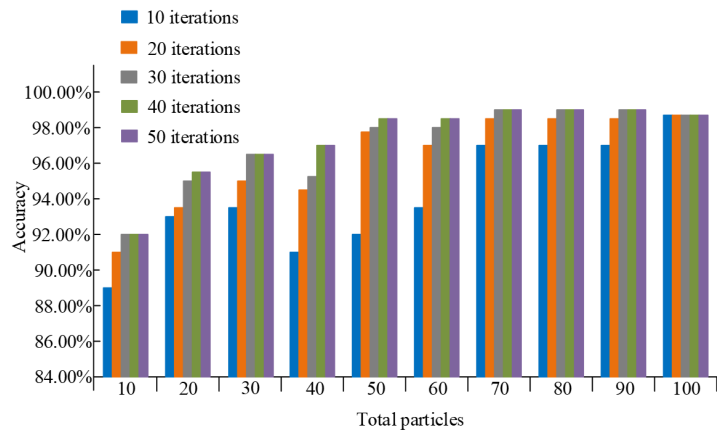
Fig. 4.1: Particle and maximum iteration value determination

Figure 4.1 shows the accuracy measurements for the maximum iteration value. The results show that when the sum of particles is the same, the greater the iterations, the higher the accuracy. When the total number of particles is 70 or more, the accuracy does not change much, all above 97%. Therefore, the study further selects the particle numbers as 70 and the max amount of iterations as 10 as the stopping criterion, sets the variable of 8 to 8, and the variable of 2 to 2. On the two-dimensional test function (ZDT3, ZDT6), the Elitist-Mutated MOPSO technique (EM-MOPSO) and Speed-constrained MOPSO (SMOPSO) algorithm were compared and tested.

Figure 4.2a and 4.2b are the comparative test diagrams of the experiments of the three algorithms on the 2D test functions ZDT3 and ZDT6. Compared with the EMMOPSO and SMOPSO algorithms, the distribution of non-inferior solutions of the proposed MOSPO algorithm is more concentrated, indicating that the algorithm has better convergence. Further, the three algorithms are compared and tested on the three-dimensional test function (DTLZ2).

Figure 4.3a- Figure 4.3c are the comparative test results of MOPSO, EMMOPSO and SMOPSO on the3D test function DTLZ2 respectively. The solution distribution of MOPSO on the 3D-test function is relatively concentrated, while EM-MOPSO and SMOPSO are relatively scattered. In summary, among the test functions of ZDT and DTLZ series, the MOPSO owns greater convergence and distribution, which shows that the algorithm has a better running effect and is an effective strategy to improve the MOPSO. The next step is to use MOPSO and genetic algorithm (GA) to provide intelligent recommendations for personalized hand hygiene behavior cultivation for children of different age groups. The accuracy rates of different indicators compared with actual data are calculated, and the accuracy results of the two algorithms are also calculated. The results are shown in Table 4.1.

Table 4.1 shows the accuracy of the indicator values of the hand hygiene behavior training recommendation algorithm and the recommendation accuracy of different algorithms. The various hand hygiene behaviors recommended by the study can meet the needs of children's hand hygiene behavior cultivation, with an accuracy rate between 80% and 100%. Compared with GA, the MOPSO algorithm provides better hand hygiene behavior recommendation results and can achieve the best hand hygiene behavior cultivation effect. The average accuracy of the MOPSO algorithm is 99.07%, while the average accuracy of the GA algorithm is 97.87%. In order to gain a deeper understanding of the developmental differences in hand hygiene behavior among school-age children and further validate the effectiveness of the designed recommendation algorithm in hand hygiene behavior cultivation, a study selected 150 high school and 150 junior high school students from a certain middle school, and 150 elementary school students from a certain primary school as subjects. These subjects were divided into three groups, and the MOPSO algorithm based health education program was used The health education program based on GA algorithm and the health education program without using the algorithm were intervened for one month. After the experiment, the recommended accuracy of different algorithms in cultivating hand
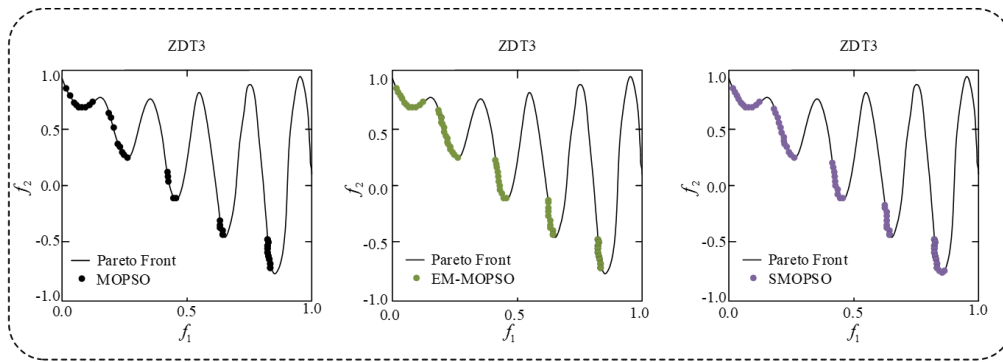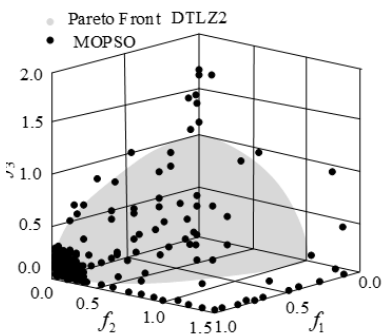
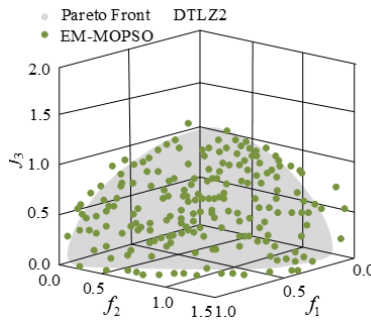(a) True Pareto edge rendering of the algorithm on the ZDT3 function
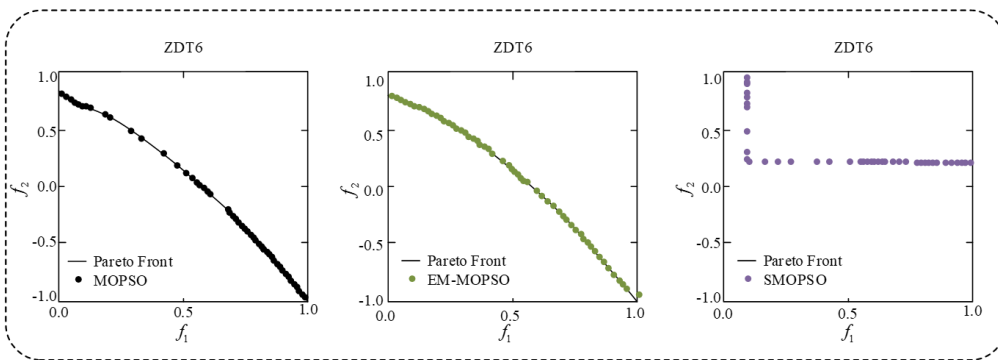
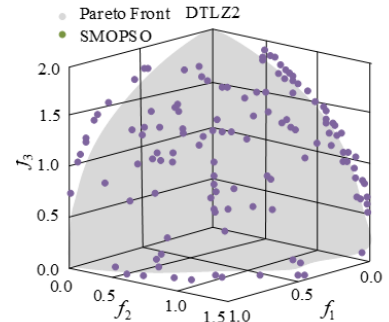(b) True Pareto edge rendering of the algorithm on the ZDT6 function

Fig. 4.2: Algorithm two-dimensional test function graph

(a) The real Pareto frontier render-ing of the MOPSO algorithm on the DTLZ2 function

(b) The real Pareto frontier render-ing of the EM-MOPSO algorithm on the DTLZ2 function

(c) The real Pareto frontier render-ing of the SMOPSO algorithm on the DTLZ2 function

Fig. 4.3: Algorithm three-dimensional test function effect diagram

Table 4.1: The accuracy of indicator values in hand hygiene behavior training recommendation algorithms and the recommendation accuracy of different algorithms

age	Accuracy of hand washing frequency (%)	Accuracy of hand washing time (%)	Accuracy of hand washing indications (%)	MOPSO algorithm accuracy (%)	GA algorithm accuracy (%)
1	97.82	98.19	99.95	99.15	97.25
2	98.50	97.67	99.89	98.76	96.52
3	99.00	98.77	99.88	99.28	97.81
4	98.67	97.59	99.82	98.69	96.32
5	99.74	95.61	99.80	98.38	95.23
6	98.54	99.19	99.99	99.50	98.05
7	98.00	98.62	97.63	99.76	98.53

Table 4.2: Recommended accuracy of different algorithms in cultivating hand hygiene behavior among students at different educational stages

Algorithm	Accuracy rate of primary school students (%)	Accuracy rate of junior high school students (%)	Accuracy rate for high school students (%)
MOPSO algorithm	94.76%	96.92%	99.07%
GA algorithm	92.35%	94.65%	97.87%
Unused	89.10%	91.32%	93.50%

hygiene behavior among students at different educational stages was calculated. The results are shown in Table 4.2.

From Table 4.2, it can be seen that after receiving the MOPSO algorithm based health education program, the recommendation accuracy of the high school student group is 99.07%, the middle school student group is 96.92%, and the accuracy of the primary school student group is 94.76%. It can be observed that as age increases, older students are more able to accurately understand and practice hand hygiene guidance. However, the MOPSO algorithm outperformed other comparison groups in all education stages, indicating that the algorithm assisted health education program has a significant effect on improving the accuracy of students' hand hygiene behavior, proving its effectiveness and emphasizing its scientific and practical significance.

4.2. Performance analysis of personalized recommendation algorithm based on multi-objective optimization model. To verify the effectiveness of a personalized recommendation algorithm for children's hand hygiene behavior development by combining multi-objective optimization models with CNN. The study extracted an appropriate amount of samples from existing databases for 500 neural network training sessions, and analyze the convergence of training errors.

Figure 4.4 is a graph of the convergence of CNN network training errors for 500 times. The results show that the error between the recommended scheme of by the CNN neural network and the user's features is between 10 -1 and 10-2, and the best training error value in training is 0.020065, which is a small error, indicating that the CNN network can be used to intelligently recommend children's hand hygiene behavior development plans that meet user needs. For exploring the performance of CNN under different data sparsity, a randomly sampled user dataset was studied, and the data sparsity was changed, and the CNN model is combined with common latent factor models (LFM) and collaborative deep learning (CDL) models. CDL language and the SIFT-LFM model using the Scale Invariant Feature Transform (SIFT) method to extract image features combined with LFM for comparative testing.

Table 4.3 shows the experimental test results of different models under different sparsity. CNN at each sparsity is more accurate than the others, and the results obtained are better. At the same time, compared with the LFM, the improvement rate of the CNN increases from 4.53% to 12.82%, which means that in When the data is sparse, the CNN is more stable than the LFM model, with less fluctuation. The research selected
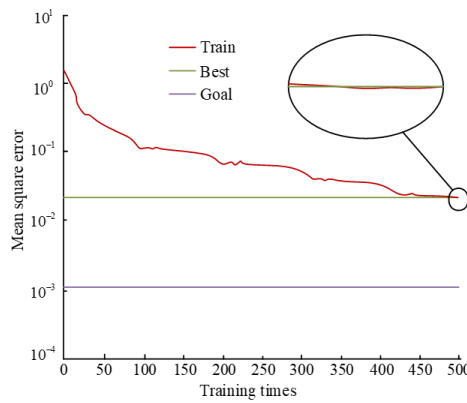
Fig. 4.4: Training Error Convergence Graph

Table 4.3: Experimental results of each model under different data sparsity

Model	Score data a d density					
	0.45%	1.37%	2.12%	2.89%	3.55%	3.93%
LFM	1.2081	1.0571	0.9837	0.9462	0.9201	0.9034
CDL	1.1654	1.0289	0.9555	0.9232	0.8978	0.8869
SIFT-LFM	1.1000	0.9903	0.9331	0.9096	0.8834	0.8759
CNN	1.0532	0.9618	0.9114	0.8873	0.8708	0.8625
Improve	12.82%	9.02%	7.35%	6.22%	5.36%	4.53%

2,000 users as test objects, and further compared the recommendation schemes of the CNN with the other three models, and used the mean absolute error (MAE) as the evaluation index. The smaller the value of MAE, the smaller the recommendation error. The result is more accurate.

Figure 4.5 is a comparison chart of the average error of the recommended schemes of the four models. The MAE value of the CNN model is smaller than that of the other three models, indicating that the CNN recommendation scheme is more accurate than other model recommendation schemes and more in line with user needs. And as the number of test users increases, the overall MAE value shows a downward trend, indicating that the larger the amount of data, the better the model's recommendation quality can be fully reflected. In summary, the personalized recommendation algorithm for children's hand hygiene behavior cultivation based on particle swarm and deep learning proposed by the above research can give the optimal personalized recommendation scheme according to user needs, further lift the life-quality of children, and meet the personalized diet of children need.

5. Discussion. In recent years, people's quality of life has significantly improved, and health education for school-age children has become more important. However, there is still a problem of non-standard hand hygiene behavior among school-age children, which may have a negative impact on their health and growth. Therefore, how to effectively cultivate correct hand hygiene behavior among school-age children has become a common concern for parents and educators. To solve this problem, a personalized recommendation scheme for hand hygiene behavior development in school-age children based on PSO and deep learning was proposed by combining MOPSO algorithm and CNN algorithm. Compared with GA, the accuracy rate of the hand hygiene behavior development in school-age children by the MOPSO algorithm is between 80% and 100%, and the average accuracy rate of its nutrient intake is 99.07%, while the mean accuracy ratio of the GA nutrient intake is 97.87%. In addition, after using the deep learning of CNN, the error of matching the recommended scheme and user features is 10 -1-10 -2, and the best training error value in training is 0.020065. When tested under different
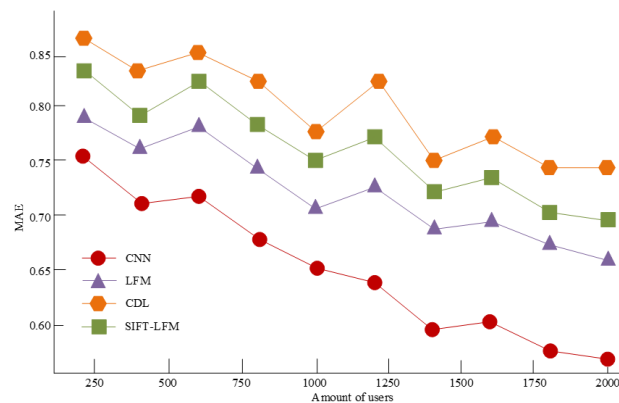
Fig. 4.5: Comparison chart of experimental results of four models

sparsity, compared with the LFM model, the improvement rate of the CNN model increased from 4.53% to 12.82%, and the performance was more stable. At the same time, the MAE value of the CNN model was smaller and the error was smaller. In summary, the above research proposes that health education programs based on PSO and deep learning can better provide personalized recommendations based on the hand hygiene behavior data of school-age children, further promoting their hand hygiene behavior development and improving their quality of life. However, current research has not taken into account the impact of different cultural backgrounds and regional differences on the hand hygiene behavior of school-age children. Subsequent research can further explore cross-cultural and cross regional plans for children's hand hygiene behavior development to meet a wider range of children's needs.

REFERENCES

[1] Ramkumar, M., Kanthlal, S. & Kumar, V. The Benefit of Passion Fruit as an Anti-ulcerogenic Diet: Scientific Evidence by In vitro and in silico H+/K+ATPase Inhibitory Activity Assessment. *Current Computer-Aided Drug Design*. **16**, 555-563 (2020)

[2] Sapkota, S., Laudari, S. & Sapkota, S. Meeting the Nutritional Needs for the Children: The Role of Fish Products from the Emerging Aquaculture of Nepal. *International Journal Of Social Sciences And Management*. **7**, 198-201 (2020)

[3] Counterpoint, K. Artificial Sweeteners for Obesity—Better than Sugar Alternatives; Potentially a Solution. *Endocrine Practice: Official Journal Of The American College Of Endocrinology And The American Association Of Clinical Endocrinologists*. **20**, 1056-1061 (0)

[4] Abdelhamid, A., Jennings, A., Hayhoe, R., Awuzudike, V. & Welch, A. High variability of food and nutrient intake exists across the Mediterranean Dietary Pattern—A systematic review. *Food Science & Nutrition*. **8**, 4907-4918 (2020)

[5] Zhou, L. & Tong, G. Research on the competitiveness and influencing factors of agricultural products trade between China and the countries along the "Belt and Road". *Alexandria Engineering Journal*. **61**, 8919-8931 (2022)

[6] Janakiraman, B. & Arumugam, S. Personalized Nutrition Recommendation for Diabetic Patients Using Optimization Techniques. *Intelligent Automation & Soft Computing*. **26**, 269-280 (2020)

[7] Tabassum, N., Rehman, A., Hamid, M., Saleem, M. & Alyas, T. Intelligent Nutrition Diet Recommender System for Diabetic's Patients. *Intelligent Automation And Soft Computing*. **30**, 319-335 (2021)

[8] Ma, M., Na, S., Wang, H., Chen, C. & Xu., J. The graph-based behavior-aware recommendation for interactive news. *Applied Intelligence.* **52**, 1913-1929 (2022)

[9] Berkani, L. Recommendation of items using a social-based collaborative filtering approach and classification techniques. *International Journal Of Data Mining, Modeling And Management.* **13**, 137-159 (2021)

[10] Benkessirat, S., Boustia, N. & Nachida, R. A New Collaborative Filtering Approach Based on Game Theory for Recommendation Systems. *Journal Of Web Engineering.* **20**, 303-326 (2021)

[11] Zhang, B., Zhang, Y., Bai, Y., Lian, J. & Li., M. Multi-dimensional recommendation scheme for social networks considering a user relationship strength perspective. *Computing And Informatics.* **39**, 105-140 (2020)

[12] Cao, B., Zhao, J., Lv, Z. & Yang, P. Diversified personalized recommendation optimization based on mobile data. *IEEE Transactions On Intelligent Transportation Systems.* **22**, 2133-2139 (2020)

[13] Zeng, Z., Sun, S., Sun, J., Yin, J. & Shen, Y. Constructing a mobile visual search framework for Dunhuang murals based on fine-tuned CNN and ontology semantic distance. *The Electronic Library.* **40**, 121-139 (2022)

[14] Wang, X., Cheng, M., Eaton, J., Hsieh, C. & Wu, S. Fake node attacks on graph convolutional networks. *Journal Of Computational And Cognitive Engineering.* **1**, 165-173 (2022)

[15] El-Shafai, W., Ali, A., El-Rabaie, E., Soliman, N., Algarni, A. & El-Samie, F. Automated COVID-19 Detection Based on Single-Image Super-Resolution and CNN Models. *Computers, Materials & Continua.* **70**, 1141-1157 (2022)

[16] Chen, Z. Research on internet security situation awareness prediction technology based on improved RBF neural network algorithm. *Journal Of Computational And Cognitive Engineering.* **1**, 103-108 (2022)

[17] Wu, J., Zhang, Y., Luo, C., Yuan, L. & Shen, X. A Modification-Free Steganography Algorithm Based on Image Classification and CNN. *International Journal Of Digital Crime And Forensics.* **13**, 47-58 (2021)

[18] Zhang, Q., Xiao, J., Tian, C., Chun-Wei Lin, J. & Zhang, S. robust deformed convolutional neural network (CNN) for image denoising. *CAAI Transactions On Intelligence Technology.* **8**, 331-342 (2023)

[19] Gbenga-Fabusiwa, F. African yam beans (Sphenostylis stenocarpa): A review of a novel tropical food plant for human nutrition, health and food security. *African Journal Of Food Science.* **15**, 33-47 (2021)

[20] Aguila, M., Ornellas, F., Research, M. & Programming, F. Parental Nutrition Influences the Structure and Function of the Organs. *International Journal Of Morphology.* **39**, 327-334 (2021)

[21] Yue, M. & Wang, X. Research on Control Strategy of Ship Energy Management System Based on Hybrid GA and PSO. *International Core Journal Of Engineering.* **6**, 185-193 (2020)

[22] Abdellah, A., Daamouche, A. & Hassan, M. Components Assignment Problem for Flow Networks Using MOPSO. *IAENG International Journal Of Computer Science.* **48**, 96-108 (2021)

[23] Ravikumar, S. & Cnn-ohgs, K. CNN-oppositional-based Henry gas solubility optimization model for autonomous vehicle control system. *Journal Of Field Robotics.* **38**, 967-979 (2021)

[24] Dhasarathan, C., Hasan, M., Islam, S., Abdullah, S., Khapre, S., Singh, D., Alsulami, A. & Alqahtani, A. User privacy prevention model using supervised federated learning-based block chain approach for internet of Medical Things. *CAAI Transactions On Intelligence TechnologyMay.* **4** (2023)

[25] Hasan, M., Islam, S., Memon, I., Ismail, A., Abdullah, S., Budati, A. & Nafi NS., A. novel resource-oriented DMA framework for internet of medical things devices in 5G network. *IEEE Transactions On Industrial InformaticsFeb.* **4**, 12 (2022)

[26] Alamri, M., Jhanjhi, N. & Humayun, M. Digital curriculum importance for new era education. *Employing Recent Technologies For Improved Digital Governance.* pp. 1-18 (2020)

[27] Khalil, M., Humayun, M. & Jhanjhi, N. COVID-19 impact on educational system globally. *Emerging Technologies For Battling Covid-19: Applications And Innovations.* pp. 257-269 (2021)

[28] Alsubaie, A., Alaithan, M., Boubaid, M. & Zaman, N. Making learning fun: Educational concepts & logics through game. *2018 20th International Conference On Advanced Communication Technology (ICACT).* pp. 454-459 (2018)